Classification of Total Load Demand Profiles for War-ships based on Pattern Recognition Methods

G.J. TSEKOURAS\textsuperscript{1}, I.S. KARANASIOU\textsuperscript{2}, F.D. KANELLOS\textsuperscript{3}

\textsuperscript{1}Department of Electrical & Computer Science, Hellenic Naval Academy
\textsuperscript{2}Informatics and Computer Science LAB, Department of Mathematics & Engineering Sciences, Univ. of Military Education - Hellenic Army Academy
\textsuperscript{3}Hellenic Transmission System Operator

Terma Hatzikyriakou, Piraeus Vari – 16673, Athens
Kastoros 72, Piraeus GREECE

Email: tsekouras_george_j@yahoo.gr, ikaran@esd.ece.ntua.gr, kanellos@mail.ntua.gr

Abstract: - The classification of total load demand profiles for every type of war-ships is crucial information, because it is the necessary base for a series of studies and operations, such as load estimation, load shedding and power management systems. In this paper a pattern recognition methodology is presented, which is based on different pattern recognition methods, such as k-means, modified k-means etc. Each method can properly be optimized by using different adequacy measures, such as the ratio of within cluster sum of squares to between cluster variation. This methodology is applied to total load demand of Hellenic Navy MEKO type frigate indicatively and the usefulness of the respective results for the power system design and operation is proved.

Key-Words: - Load profiles, clustering algorithms, pattern recognition, adequacy measures, warship

1 Introduction

The power system of a warship, such as a frigate or a corvette, is a crucial parameter for its fighting preparedness. Especially, during the last decade in the framework of All Electric Ship (AES) a series of advantages is offered such as increased safety, survivability, manoeuvrability, precise and smooth speed control, reduced machinery space, low operation and maintenance costs, low noise and low pollutant emission levels [1]. These benefits are already obvious in warships such as aircraft-carriers and submarines, which have a total electrified power system design based on nuclear reactors and batteries correspondingly.

The power system design and operation under different ship operating condition (anchor, floating, navigating, fighting, etc) is a complicated process, which requires the total load demand as data. The usual solution of this problem is the estimation of the total load demand for each operating condition based on multiplicative factors for each electric consumer, such as power efficiency, load factor, for each ship operating condition in order to calculate the average daily required load, as it has been analyzed in [2]-[3]. Alternatively, characteristic total load demand curves for each operating condition can be estimated through classification process. In order to carry out this classification, the chronological load curves per day or smaller time divisions can be used.

During the last years, a significant research effort has been devoted to load curves classification, in order to solve the short-term load forecasting of anomalous days [4], to cluster the customers of the power systems [5] and to estimate the total load profile of power systems for the implementation of demand side management programs [6-7]. The clustering methods used so far are the k-means [4]-[6], the fuzzy k-means [4]-[6], the self-organizing map [4]-[6], the “modified follow the leader” [4], and the hierarchical methods [4]-[6]. These methods generally belong to pattern recognition techniques [8]. The most commonly used respective adequacy measures are the mean index adequacy [9], the clustering dispersion indicator [4], [9], the similarity matrix indicator [9], the Davies-Bouldin indicator [4], [9], the modified Dunn index [4], [9], the scatter index [4], the mean square error [9] and the ratio of within cluster sum of squares to between cluster variation [7].

The objective of this paper is to present a pattern recognition methodology for the classification of the daily chronological total load demand curves for war-ships power systems. It compares the results obtained by certain clustering techniques (such as k-means with special weights initialization and adaptive vector quantization) using the ratio of within cluster sum of squares to between cluster variation as adequacy measure. Following, the developed methodology is applied for the active
total load demand of the Hellenic Navy MEKO type frigate for a period of 20 days. Finally, the implementations of the respective results (typical days and representative load curves) in navy aspects are synoptically analyzed.

2 Pattern Recognition Methodology for the Classification of Total Load Demand Curves of Warship’s Power System

The classification of chronological load curves for power system of a war-ship is achieved by applying the pattern recognition methodology, as shown in Fig. 1.

- Data and features selection: The active energy $E$ and reactive energy $E_Q$ values are registered (in kWh and kvarh respectively) for each time period in time steps $Dt$ (which can be 1 hour, 15 mins, etc). The chronological load curves are determined for the study period, as the respective active power $P$ and reactive power $Q$ are calculated by:

$$ P = \frac{E}{Dt} $$

$$ Q = \frac{E_Q}{Dt} $$

- Data preprocessing: The load diagrams are examined for normality, in order to modify or delete the values that are obviously wrong. This process is known as noise suppression.

- Main procedure of pattern recognition methods: For the load diagrams, a number of clustering algorithms can be applied, such as k-means, fuzzy k-means, adaptive vector quantization, self-organized map and hierarchical clustering. Here, the study is limited to k-means and adaptive vector quantization algorithms. Each algorithm can be trained for the set of load diagrams and evaluated according to different adequacy measures, such as mean square error, mean index adequacy, clustering dispersion indicator, similarity matrix indicator, Davies-Bouldin indicator and ratio of within cluster sum of squares to between cluster variation. Here, the study is limited to last one, because it is expected to be the most descriptive adequacy measure as it has been explained in [7]. The parameters of the algorithms are optimized, if necessary. The developed methodology uses the clustering method that provides the most satisfactory results.

The results of the developed methodology can have various applications, as it is analyzed in section 5.

3 Mathematical Base of Pattern Recognition Methodology

3.1 General

Generally $N$ is defined as the population of the input vectors, which are going to be clustered. In this case study the input vector is the chronological total load demand of a war-ship’s power ship. The $\bar{x}_i = (x_{i1}, x_{i2}, ..., x_{id})^T$ symbolizes the $\ell$-th input vector and $d$ its dimension, which equals to 24, if the load measurements are taken every hour, or 96, if the respective measurements are taken every 15 minutes. The corresponding set is given by $X = \{\bar{x}_i : \ell = 1, ..., N\}$. Each classification process
makes a partition of the initial $N$ input vectors to $M$ clusters. The $j$-th cluster has a representative, which is the respective load profile and is represented by the vector $\mathbf{w}_j = \left(w_{j1}, w_{j2}, ..., w_{jd}\right)^T$ of $d$ dimension. The vector $\mathbf{w}_j$ expresses the cluster center. The corresponding set is the classes set, which is defined by $\mathcal{W} = \{\mathbf{w}_j, k = 1, ..., M\}$. The subset of input vectors $\mathbf{x}_i$, which belong to the $j$-th cluster, is $\Omega_j$ and the respective population of load diagrams is $N_j$. For the study and evaluation of classification algorithms the Euclidean distance is used [4].

### 3.2 K-means model

The k-means clustering method groups the set of the $N$ input vectors to $M$ clusters using an iterative procedure. Initially the weights of the $M$ clusters are determined. In the classical model a random choice among the input vectors is used [4]. In the developed algorithm the $w_{jl}$ of the $j$-th center is initialized as:

$$w_{jl}(0) = a + b \cdot (j - 1)/(M - 1)$$

where $a$ and $b$ are properly calibrated parameters. During epoch $t$ for each training vector $\mathbf{x}_i$ its Euclidean distances $d(\mathbf{x}_i, \mathbf{w}_j)$ are calculated for all centers. The $\ell$-th input vector is put in the set $\Omega_j^{(\ell)}$, for which the distance between $\mathbf{x}_i$ and the respective center is minimum. When the entire training set is formed, the new weights of each center are calculated as:

$$\mathbf{w}_l^{(t+1)} = \frac{1}{N_j^{(t)}} \sum_{\mathbf{x}_i \in \Omega_j^{(t)}} \mathbf{x}_i$$

where $N_j^{(t)}$ is the population of the respective set $\Omega_j^{(t)}$ during epoch $t$. This process is repeated until the maximum number of iterations is used or the variation of the weights is not significant. The algorithm’s main purpose is to minimize the error function:

$$J = \frac{1}{N} \sum_{t=1}^{N} d^2(\mathbf{x}_i, \mathbf{w}_{k(t)} \in \Omega_k)$$

The main difference compared to the classical model is that the process is repeated for different pairs of $(a,b)$ and the results of the pair $(a,b)$ with the best WCBCR are recorded.

### 3.3 Adaptive vector quantization

This algorithm is a variation of the k-means method, which belongs to the unsupervised one-layer neural networks. It classifies input vectors into clusters by using a competitive layer with a constant number of neurons. During epoch $t$ each input vector $\mathbf{x}_i$ is randomly presented and its respective Euclidean distances from every neuron are calculated. The weights of the winning neuron (with the smallest distance) are updated as:

$$\mathbf{w}_l^{(t+1)}(n) = \mathbf{w}_l^{(t)}(n) + \eta(t) \cdot (\mathbf{x}_i - \mathbf{w}_l^{(t)}(n))$$

where $n$ is the number of input vectors, which have been presented during the current epoch, $w_{jl}^{(0)} = 0.5, \forall j, i$ and $\eta(t)$ is the learning rate according to:

$$\eta(t) = \eta_0 \cdot \exp\left(-t/T_{\eta}\right) > \eta_{\min}$$

where $\eta_0$, $\eta_{\min}$, and $T_{\eta}$ are the initial value, the minimum value and the time parameter respectively. The remaining neurons are unchangeable for $\mathbf{x}_i$, as introduced by the Kohonen winner-take-all learning rule [10]. This process is repeated until either the maximum number of epochs is reached or the
weights converge or the appropriate error function is not improving.

4 Application of the Proposed Methodology

4.1 Case study

The developed methodology is applied for the total load demand of the Hellenic Navy MEKO type frigate. The active energy of ship’s generators was registered by the control and monitoring system “NAUTOS” every 15 minutes for a period of 20 days (8-31 January 1998) with the ship at “shore” condition. This load is equal to the total load demand provided no electric power connection with the shore. The respective daily vector dimension is equal to 96. In the next paragraphs the application of each clustering method is analyzed.

4.2 Application of the k-means

The proposed model of the k-means method is executed for different pairs \((a,b)\) from 2 to 20 clusters, where \(a=\{0.00, 0.11, \ldots, 0.45\}\) and \(a+b=\{0.55, 0.56, \ldots, 1.00\}\). For each cluster 2116 different pairs \((a,b)\) are examined and the pair with the smallest \(WCBCR\) is selected. In Fig. 2 the \(WCBCR\) measure for 2 to 20 clusters is presented for the set of 20 training patterns of the total load demand.

![Fig. 2. WCBCR measure of the k-mean for 2 to 20 clusters for the set of 20 training patterns of the total load demand](image)

The number of the clusters, which provides satisfactory results for the study of the frigate’s total load demand, corresponds to the knee of the respective curve [5], as it is shown in Fig. 3. In this case the respective number is superior than 3, so the proposed number of clusters is 4.

If the axis of \(WCBCR\) changes so that the respective scale is extended, Fig. 4 will be arisen and the respective number of clusters should be equal to 7. This proves that the graphical solution is not unique and the user’s knowledge is also necessary.

![Fig. 3. The use of tangents for the estimation of the knee based on WCBCR measure of the k-mean for 2 to 20 clusters for the set of 20 training patterns of the total load demand](image)

![Fig. 4. The use of tangents for the estimation of the knee based on WCBCR measure of the k-mean for 2 to 20 clusters for the set of 20 training patterns of the total load demand with enlargement of Fig. 3](image)

The alternative model is the classical one with the random choice of the input vectors during the centers’ initialization. For the k-means model 100 executions are carried out and the best results for each index are registered. The superiority of the proposed model applies in all cases of neurons, while a second advantage is the convergence to the same results for the respective pairs \((a,b)\), which can not be achieved using the classical model. The respective superiority is presented in Fig. 5.

4.3 Application of adaptive vector quantization (AVQ)

The initial value \(\eta_0\), the minimum value \(\eta_{\text{min}}\) and the time parameter \(T_{\eta_0}\) of learning rate must be properly
 calibrated. In this case the respective values of the parameters are \( \eta_0 = \{0.1, 0.2, \ldots, 0.9\}, \quad \eta_{\text{min}} = \{0.00001, 0.00005, 0.0001, 0.001\} \) and the time parameter \( T_\phi = \{500, 1000, \ldots, 5000\} \). It is noted that the \( \eta_{\text{min}} \) value does not practically improve the neural network’s behavior assuming that it ranges between \( 10^{-5} \) and \( 10^{-6} \). In Fig. 5 the WCBCR measure for 2 to 20 clusters is presented for the respective data set for the best combination (\( \eta_0, T_\phi, \eta_{\text{min}} \)) of each cluster.

### 4.4 Comparison of clustering models

In Fig. 5 the best results achieved by each clustering method (proposed k-means, classical k-means, adaptive vector quantization) for WCBCR measure are depicted. The proposed k-means model has the smallest values in the whole width of the clusters’ interval.

![Fig. 5. WCBCR measure of the proposed k-means technique, the classical k-means technique and adaptive vector quantization algorithm for 2 to 20 clusters for the set of 20 training patterns of the total load demand.](image)

The improvement of the WCBCR measure is significant until 10 clusters. After this value the behavior is practically stabilized. It is noted that dead clusters are appeared over 11 clusters. After 15 clusters a small improvement is presented.

Having also taken into consideration that the analogy of the computational training time for the under study methods is 0.08:1:30 (classical k-means: proposed k-means: AVQ), the use of the k-means model is proposed. It is mentioned that the computational training time for the proposed k-means method is approximately 1.5 minutes for a Pentium 4, 1.7 GHz, 768 MB.

### 4.5 Representative daily total load demand curves of the HN MEKO type frigate power system at “shore” condition

The results of the respective clustering for 4, 7 and 10 clusters using the proposed k-means model with the optimization of the WCBCR measure are presented in Table 1, where the calendar of the time period under study with the kind of cluster and the total number of days per cluster are registered. It is observed that using 4 clusters for the classification the third cluster is the most populated one. Using 7 or 10 clusters for the classification the third cluster of the classification with 4 clusters has been divided in separate new clusters. This is obvious, as the first cluster, the second one and the last one for the three different classifications are practically unchangeable.

<table>
<thead>
<tr>
<th>Date (January 1998)</th>
<th>Number of clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4 ((1^{st}-4^{th}))</td>
</tr>
<tr>
<td>8</td>
<td>2(^{nd})</td>
</tr>
<tr>
<td>9</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>11</td>
<td>2(^{nd})</td>
</tr>
<tr>
<td>12</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>14</td>
<td>4(^{th})</td>
</tr>
<tr>
<td>16</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>17</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>18</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>20</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>21</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>22</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>23</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>24</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>25</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>26</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>27</td>
<td>2(^{nd})</td>
</tr>
<tr>
<td>28</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>29</td>
<td>1(^{st})</td>
</tr>
<tr>
<td>30</td>
<td>3(^{rd})</td>
</tr>
<tr>
<td>31</td>
<td>3(^{rd})</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total number of days per cluster</th>
<th>1(^{st})</th>
<th>2(^{nd})</th>
<th>3(^{rd})</th>
<th>4(^{th})</th>
<th>5(^{th})</th>
<th>6(^{th})</th>
<th>7(^{th})</th>
<th>8(^{th})</th>
<th>9(^{th})</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>2</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>7</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Fig. 6 the representative load curves per cluster are presented using the classification with 4 clusters.
Additionally the confidence limits of the variations (mean value ± standard deviation) are presented and this has a probability of occurrence equal to 68.27% assuming a normal distribution.

![Graphs showing load curves for 4 clusters.](image)

Fig. 6. Daily chronological load curve for total load demand with the respective standard deviation using the proposed k-means technique algorithm with WCBCR measure for 4 clusters.

Specifically, the first cluster represents the load curve of 29 January 1998, because the frigate was supplied by shore with power for 8 hours. This cluster remains unchangeable in all under study classifications. The second cluster represents days with small mean load demand, while the third one is the most populated one with mean total load demand about 530 MW and with mean standard deviation about 40 MW. The fourth cluster is the last cluster, which represents the load curve of 14 January 1998, where a power system’s failure was arisen at 10:45 p.m. This day always remains in a separate cluster, as it is a special day, which could be deleted during the data preprocessing. From the analysis of this short period it is likely that during workdays and no-workdays the frigate’s power system has not present different behavior in opposition to what happens in intercontinental power system [7].

5 Practical Application of Classification Methodology

The results of the developed methodology can be used either for power system design or for power system operation. More specifically:

- the design of the warship’s power system estimating the respective total load demand more accurately and selecting the generators properly. The optimized power system’s design increases safety and survivability, it reduces machinery space, while it can allow low operation and maintenance costs, low noise and low pollutant emission levels.
- the operation of the warship’s power system succeeding more precise short-term load forecasting, increasing the respective operation reliability and decreasing the respective operation cost.
- the improvement of power factor taking into consideration the respective reactive load curves.
- the load estimation after the application of demand side management programs for total load demand, as well as the feasibility studies of the energy efficiency which normalize the total load demand and improve the total load factor.
- the improvement of the operation of the automatic battle management and load shedding systems, because the automatic supply of the critical consumers in each operating mode is facilitated in case of power system’s fault based on the available generators, the healthy part of the power distribution system and the load demand of each consumer. This improves the crucial parameter of ship’s fighting preparedness and
respective survivability.

6 Conclusions

This paper presents a pattern recognition methodology for the study of the total load demand behavior of war-ships’ power systems. The unsupervised clustering methods can be applied, such as the k-means and adaptive vector quantization. The performance of these methods is evaluated by the ratio of within cluster sum of squares to between cluster variation. Finally the representative daily load diagrams along with the respective populations per each typical day are calculated. This information is valuable for the shipbuilding companies and Navies, because it mainly facilitates (1) the design of the warship’s power system optimizing the generators’ selection and minimizing the machinery space, (2) the operation of the warship’s power system through the correct load estimation increasing the energy efficiency and minimizing the operation cost, (3) the operation of the automatic battle management and load shedding systems increasing fighting preparedness and respective survivability.

By applying the proposed methodology to the active total load demand of the Hellenic Navy MEKO type frigate for a period of 20 days the respective primary results have been presented.

In future more extended data sets will be examined so that safer results can be arisen. Contemporaneously, additional unsupervised clustering methods can be applied, such as the fuzzy k-means, hierarchical methods, mono-dimensional and bi-dimensional self organizing maps, while their performance can be evaluated by other adequacy measures, such as mean square error, mean index adequacy, clustering dispersion indicator, similarity matrix indicator, Davies-Bouldin indicator. Additionally, different time periods of chronological load curves (beyond the daily ones) can be also investigated.

Acknowledgements

The authors want to express their sincere gratitude to the Hellenic Navy for providing all the necessary data for this application.

References: